Employee Dilemmas From Competing Organizational Objectives: Insights from Emergency Medical Services

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Abstract
The literature on multiple-goal organizations highlights the unique challenge of simultaneously meeting potentially conflicting financial and prosocial objectives. In this paper, we study how frontline employees deal with these competing demands within the context of Emergency Medical Service (EMS) crews responding to 9-1-1 calls. Using data from 31 states reported to the US National Emergency Medical Services Information System, we find that even in the absence of direct and immediate individual financial incentives, EMS crews are responsive to the financial objective of their agencies by providing higher levels of service to patients with higher ability to pay. We find that both private insurance and Medicare patients receive more procedures (4.6% and 1.5%) and have longer transport times (5.1% and 3.9%) than Medicaid patients controlling for time, call, patient, and condition characteristics. However, we also find evidence suggesting that EMS crews dynamically vacillate between organizational objectives between calls, depending on the context and the salience of the objective. We find these ability to pay differences increase on busy days when the financial opportunity costs are high, and when their employing agency has stronger financial need. However, disparities decrease significantly when calls are life-threatening, as patient needs overcome financial considerations. Surprisingly, these patterns hold across organizational forms including public, private, and non-profit organizations.

1. INTRODUCTION

Effectively managing highly autonomous employees is key to organizational performance in knowledge or skill-intensive industries (Campbell et al. 2012; Coff 1997; Lippman & Rumelt 1982). However, while autonomy itself presents the organization with difficult challenges in managing individual-level human capital (e.g., Coff 1997, Gambardella, Panico, & Valentini 2018; Grossman and Hart 1983), the modern reality is that organizations also pursue multiple potentially conflicting objectives simultaneously, often with no clear priority among them (Cyert and March 1963; Simon 1972; Battilana & Lee 2014; Battilana et al., 2015; Doherty et al. 2014; Pache & Santos 2013; Obloj & Sengul, 2020). In the presence of autonomy, multiple objectives can lead to confusion, loss of focus, and multi-tasking problems as individuals seek to maximize on multiple dimensions (Jensen 2002; Obloj & Sengul 2020; Ethiraj & Levinthal 2009; Hu & Bettis 2018; Pache & Santos 2010, Holmstrom and Milgrom 1991). Multiple organizational objectives likewise compound the typical challenges faced with designing and implementing incentive schemes to reward employee behaviors in achieving firm-level objectives (e.g., Holmstrom 1979; Kerr 1975; Gubler, Larkin, and Pierce 2016; Obloj & Sengul 2020; Zenger 1994), leaving organizations with only limited levers to direct and reward autonomous employees. In the presence of multiple objectives and individual autonomy, it consequently remains unclear how organizations can most effectively manage human capital to achieve the various objectives of the organization.

In this paper we investigate how unincentivized organization-level financial and social objectives combine to influence care given by Emergency Medical Service (EMS) professionals during 9-1-1 calls. We argue that EMS professionals will use their autonomy during emergency calls to dynamically adjust their behaviors to respond to organization-level objectives, even absent direct financial incentives or clear direction from management to do so. This adjustment is driven by the salience of the organization-level objective during the call, by individual and organization-level social objectives, and by organization-level financial incentives that trickle down to indirectly influence professionals. The result is that EMS agencies are able to pursue multiple conflicting organization-level objectives simultaneously without providing direct incentives more effectively than vacillating in their focus at the organization-level between conflicting objectives or trying to reward both objectives simultaneously.

Specifically, we argue that in cases where strong incentives are not provided to employees on any single dimension, employees may use their autonomy to dynamically oscillate between organizational priorities in a way that leads to both priorities being achieved simultaneously. EMS personnel are generally intrinsically motivated towards patient wellbeing, do not benefit directly from patient payments on account of their salary, and often do not know with certainty how patients will pay during a 9-1-1 call. However, EMS agencies must simultaneously satisfy a prosocial health mission while staying financially viable (Berwick et al. 2008; Roth et al. 2019). Financial concerns are prevalent in EMS agencies because of governmental underfunding, an inability by law to refuse emergency care, and below cost reimbursements provided by some insurance providers, including Medicaid and to a lesser extent Medicare (NEMSAC 2016; CMS 2019; Munjal et. al 2019). We argue that these financial challenges will create organization-level incentives for EMS agencies to treat patients differently depending on ability to pay, and that these incentives will trickle down to influence professional behavior on calls. EMS professionals consequently will take actions to capture more value from high ability to pay patients, that will not be evident with lower ability to pay patients. These actions will increase when the agency is in more financial need and when the opportunity cost of serving a low ability to pay patient is high, as this increases the salience of the organization-level financial objective. Conversely, when patient health needs are critical, and the social health objective of EMS is more salient, we expect these differences to disappear. Thus, the aspects of the context, and the salience of the objective to employees at any given moment, can influence their behaviors and decision making of autonomous professionals in unanticipated ways unexplored in the current literature.

To test these arguments, we draw on a national multi-year (2012-2016) sample of EMS data for 31 states from the US National Emergency Medical Services Information System (NEMSIS). We exploit quasi-random assignment of patients (and their corresponding ability to pay) to EMS crews in a given geographic service area and investigate within-unit care responses to differences in patient ability to pay. After controlling for call and patient characteristics, location effects, and time effects, our unit fixed effect models suggest that EMS personnel: 1) spend more time on calls with private insurance patients than with lower ability to pay Medicare (3.9% difference) and Medicaid patients (5.1% difference), and 2) perform more medical procedures for private insurance patients than patients paying with Medicare (1.5% difference) and Medicaid (4.6% difference). These differences increase for units on days with higher call volumes, when the opportunity cost of serving a low paying patient is higher, and during periods when an agency serves more low ability to pay patients in the recent past. Conversely, we find that care disparities from ability to pay are reduced when EMS professionals respond to urgent calls with more serious patient health needs. Robustness checks indicate our results hold with instrumental variables estimation; when controlling for patient preferences, location, traffic patterns, and patient health conditions; under alternative empirical specifications; and with different data subsamples. Together, these findings suggest that patient ability to pay significantly influences EMS professional care decisions. However, the magnitude of the effect is influenced by contextual factors that increase or decrease the salience of organizational objectives.

These findings contribute generally to the nascent but growing literature on challenges faced by multiple-goals organizations (e.g., Battilana & Lee 2014; Battilana et al., 2015; 2020; Doherty et al. 2014; Ethiraj & Levinthal, 2009; Pache & Santos 2013; Obloj & Sengul, 2020), and specifically to work on conflicting prosocial and financial objectives. Existing work has largely focused on organizational outcomes, on managers, or other directly incentivized individuals (e.g., Cooper, 2021; Obloj & Sengul, 2020; Gaba & Greve, 2019). Our study highlights that even unincentivized workers can face dilemmas from multiple objectives, which may influence their behaviors in unanticipated ways. However, unlike organizations or managers, workers may dynamically adjust their focus between competing organizational priorities in ways that allow them to pursue both objectives simultaneously.

Second, our results contribute to literatures on incentive-performance links in multiple-goal organizations, and in contexts where intrinsic motivation towards one dimension is high (e.g., Ryan & Deci 2000; Besley & Ghatak 2018; Prendergast 2008). This responds directly to the call from Battilana and Lee (2014, Page 419) to "examine the influence of different performance measures and incentive systems on hybrids' sustainability and performance both in the commercial and social realms." In our context EMS personnel are typically highly intrinsically motivated towards the social mission of EMS and do not face direct or immediate financial incentives. However, we find that organizational-level financial incentives trickle down in unanticipated ways to provide indirect financial incentives to professionals, which influences patient care decisions and the financial viability of the agency. This result pattern is evident and impactful across organization types (i.e. public, for-profit, volunteer).

Third, our findings contribute to the growing discussion around healthcare inequities and care disparities in healthcare (e.g., Chetty et al. 2016; Gaffney & McCormick 2017; Shroeder 2007; Nelson 2002). While some scholars have focused on care disparities driven by differential patient remuneration (Gruber & Owings 1994; Gruber, Kim, & Mayzlin 1999; Delgado et al. 2014; Larkin et al. 2017), our results suggest that even unincentivized employees can respond to differences in patient ability to pay, through the indirect incentives provided by organizational-level incentives.

Finally, these findings have important implications for managers and policy makers. They suggest managers must monitor employee decision-making when employees face multiple conflicting organizational objectives (e.g., Battilana & Lee 2014; Doherty et al. 2014). This is likely particularly important when organization financial needs are salient to employees, and when employees have significant discretion in their work (i.e., Lipsky 2010; Teece 2003). Managers of multiple-objective organizations must also realize that structured compensation systems, which do not directly reward employees based on performance, may still engender similar issues. At a policy level, our results suggest that policymakers would be well-served to consider the potential indirect incentives provided to healthcare professionals via below cost reimbursements from public insurance.

2. | THEORETICAL DEVELOPMENT

2.1 | The Challenge of Multiple Organizational Objectives

Modern organizations often pursue multiple objectives simultaneously, often with no clear priority among them (Cyert and March 1963; Simon 1972; Battilana & Lee 2014; Battilana et al., 2015; Doherty et al. 2014; Pache & Santos 2013; Obloj & Sengul, 2020). These objectives may be imposed by external or internal stakeholders (Margolis & Walsh, 2003), and often exist in tension with each other. Multiple objectives present potentially difficult problems for organizations and their managers, as they may be unable to simultaneously maximize along more than one dimension (Jensen 2002; Obloj & Sengul 2020) and may consequently encounter confusion or "performance freezes" as they seek to pursue multiple objectives (Ethiraj & Levinthal, 2009; Hu & Bettis, 2018; Pache & Santos, 2010). Emphasizing a social objective, for instance, may result in organizations losing sight of financial outcomes and risking bankruptcy (Pache, Battilana, & Spencer, 2019). However, emphasizing a financial objective may result in "mission drift" and hurt the organization's legitimacy among stakeholders (Grimes, Williams, & Zhao, 2019).

While prior work has shed light on the performance challenges of multiple objectives for organizations (Battilana et al., 2015; Pache and Santos, 2012; Obloj & Sengul, 2020), including how incentivized employees and managers respond to these challenges (e.g., Cooper, 2021; Gaba and Greve, 2019), significantly less work has focused on potential dilemmas imposed on unincentivized frontline workers by multiple organizational objectives. When companies embrace both a financial and social objective, for instance, it may lead to complexity and confusion by employees as they seek to grapple with potentially conflicting goals (Battliana et al., 2020). While some scholars have argued that the solution lies in training programs, incentives, and other controls systems, which may provide clarity around how behaviors are assessed and rewarded on multiple dimensions (Battliana Lee, 2014), in practice a long literature has shown the difficulties and potential pitfalls of such efforts (e.g., Baker 1992; Gubler, Larkin, and Pierce 2016; Holmstrom and Milgrom 1991; Kerr 1975; Larkin, Pierce, and Gino 2012).

In this paper we focus on a single setting to understand how Emergency Medical Service (EMS) personnel balance and respond to competing organizational objectives, and how aspects of the context might create indirect incentives that influence EMS professional on-the-call behaviors. We argue that organization-level financial objectives create indirect financial incentives that trickle down to influence EMS personnel behaviors on emergency calls. However, because they are given significant decision-making autonomy on emergency calls, and do not experience direct financial incentives on any single dimension, EMS professionals dynamically adjust their behavior between calls to pursue both financial and social organizational-level objectives simultaneously, depending on the context and salience of the organization objective, in ways previously unanticipated in the literature. This ultimately allows the organization to achieve both conflicting objectives more effectively than when trying to vacillate in focus between organizational priorities, or by developing incentive systems that reward multiple organizational-level objectives simultaneously.

2.2 | EMS Crew Performance Given Competing Organizational Objectives

EMS agencies respond to health emergencies following 9-1-1 calls and are responsible for stabilizing and delivering patients to healthcare facilities. Of the 22 million nationwide 9-1-1 calls in 2016, 14.6 million US patients were transported to hospitals by EMS units (Munjal et al. 2019). A 2013 survey of

1300 US emergency departments found that 17% of patients arrived at US emergency departments by ambulance (Augustine 2014). EMS agencies are state-regulated and typically operate multiple EMS units (e.g., ambulances and crews) within a stable geographic area. Units are dispatched to patients—either from agency buildings or from strategic waiting locations—by call dispatch centers following 9-1-1 calls. Once on scene, and patient condition is assessed, EMS crews make transport decisions in conjunction with patients or other supporting parties. If transport occurs EMS personnel may administer medications and perform medical procedures while en route to the hospital to care for patient health needs.

EMS agencies, regardless of their organizational form (i.e. public, private, volunteer, etc.) must simultaneously satisfy multiple potentially conflicting objectives, including their prosocial health mission while staying financially viable (Berwick et al. 2008; Roth et al. 2019). EMS agencies typically receive limited public funding and struggle with chronic underfunding (CMS 2019; NEMSAC 2016; Munjal et al. 2019). Common EMS agency types include community/charity (non-profit), governmental (non-fire), hospital-affiliated, private (non-hospital), and integrated fire departments. Regardless of type, public underfunding necessitates a reliance on self-generated revenues to maintain and improve agency operations and subsequently to carry out their health objective (NEMSAC 2016). Such revenues primarily stem from patient insurance payments. While private insurers typically cover more than the full cost of care for an EMS call, Medicare and Medicaid usually reimburse at or below cost and typically do not reimburse for procedures (GAO 2007, 2012; NEMSAC 2016). Reimbursement coverage and amounts normally decrease in the following order: private insurance, Medicare, and Medicaid. The main variable billing components for an EMS call include transport fees per mile and fees for procedures provided.

Limited public funding to agencies and the insurance remuneration structure create strong organization-level incentives for EMS agencies to recoup losses, where possible, from high-paying patients. This should particularly be the case in areas where financial funding is most limited and for agencies that typically respond to a high proportion of public insurance calls, relative to private insurance calls. To satisfy contractual obligations and carry out their health objective requires adequate financial resources. However, limited funding and the inability of EMS agencies to refuse care by law for low-paying patients, regardless of organizational type (public, private, non-profit), creates organization-level financial challenges in carrying out their health objective.

While patient ability to pay directly influences EMS agency revenues and consequently generates strong organization-level incentives towards actions that will improve the financial situation of the agency, there are reasons to believe that this should not impact EMS personnel decisions directly. First, EMS personnel are typically salaried (CMS 2019; USBLS 2020), and thus do not have direct and immediate financial incentives related to call performance or patient ability to pay (CMS 2020). Without such incentives, EMS personnel may disregard patient ability to pay on calls, knowing their compensation is fixed regardless, and instead primarily focus on patient health outcomes. Second, as professional healthcare providers EMS personnel are often highly intrinsically motivated towards the health objective of emergency medical services.[1] They may therefore act in the best interest of patients regardless of financial remuneration in an effort to improve patient health outcomes. The Hippocratic Oath and other healthcare ethical guidelines and norms support this patient health focus. Finally, patient insurance information may not always be clearly revealed to EMS personnel during the course of a call.[2] Without clear and convenient information on insurance, EMS professionals may focus more on patient health than patient ability to pay.

[1] Informal discussions with EMS personnel revealed that a desire to help others and to improve patient health outcomes was a strong determinant of their career choice and remains an important daily motivator to perform their job well.
[2] Informal correspondence with several EMS agency directors indicated that EMS crews are instructed not to solicit insurance information and such information is revealed only by patient choice.

While the above points suggest patient ability to pay is unlikely to influence EMS personnel decisions during an emergency call, there are also important reasons suggesting otherwise. First, even though EMS personnel do not typically have direct financial incentives associated with patient remuneration or on-call performance, patient ability to pay may influence EMS personnel indirectly in the long term through their agency. The solvency and growth of the EMS agency, worker job security, future wage increases, and equipment purchases are all influenced by agency revenues. Thus, while patient remuneration does not influence personnel take home pay for a given call, in the long run it accumulates to ultimately determine the financial solvency and success of the agency in which they are employed. This indirectly affects worker job prospects and take-home pay in the long term. Second, intrinsically-motivated EMS personnel may be more committed to the health objective of EMS agencies. However, they realize that financial resources are critical to the success of this objective (e.g., Battilana & Lee 2014; Doherty et al. 2014; Pache & Santos 2013). Thus, taking actions on a call that increase financial resources aids in the long-term viability of the EMS health objective.

The above suggests that organizational-level incentives may trickle down to influence EMS personnel decisions based on patient ability to pay, even absent direct financial incentives. This is driven by the dual objective nature of EMS agencies and the indirect incentives it provides to intrinsically-motivated EMS personnel (e.g., Ryan & Deci 2000; Besley & Ghatak 2018; Prendergast 2008). EMS professionals may act to ensure the financial viability of their agency in the long run by spending more time with and providing more procedures for higher-paying patients compared to lower-paying patients. This increases the call insurance bill for private insurance patients compared to publicly-insured patients, whose insurance is often reimbursing at or below cost. Our first hypothesis follows:

Hypothesis (H1): *Perceived patient ability to pay via insurance leads to differential EMS service provision such that patients who have private insurance will experience longer transport times and receive more procedures relative to lower-paying public insurance patients.*

2.3 | Urgent Patient Health Needs Increase the Salience of the Social Objective

While the preceding logic suggests patient ability to pay will lead to care disparities during EMS calls on average based on patient ability to pay, the underlying mechanisms specified above also imply cases where this effect is likely to be stronger or weaker. This primarily relates to the salience and relative strength of organizational-level financial incentives felt by EMS professionals on an emergency call relative to the motivating strength of the health objective.

First, we expect financial incentives to have lower relative strength on a call (compared to the health objective) when the patient's health condition is critical, and consequently the need for transport and care at the hospital is urgent. In such cases patient health outcomes are directly influenced by time, and any delay in the transportation process and treatment can potentially jeopardize patient wellbeing or survival (Holmén et al., 2020; O'Keeffe et al., 2011). Procedures performed en route in such cases are in an attempt to improve the patient's condition during transport and to prepare them for care at the emergency department. In these cases, the EMS unit generally uses lights and sirens to shorten the time needed to safely transport the patient to the hospital. In such cases patient health needs overshadow any consideration about patient ability to pay, or the long-term financial viability of the agency, and instead push EMS professionals to focus entirely on patient health outcomes.

Conversely, when the patient's health condition is less critical, and transport and care urgency is relatively lower, the strength of indirect financial incentives relative to the health objective increases. In these cases, patient health (and subsequently the health objective of the organization) is not significantly harmed by taking actions on the margin that improve the long-term financial situation of the agency. This may include spending more time with higher-paying patients by driving to a slightly farther hospital or performing additional procedures. While not negatively influencing patient outcomes, such actions may improve the long-term financial viability of the agency, as it increases the amount billed to the patient's insurance. Thus, we expect care disparities to be relatively small when patient health needs are critical and calls are urgent, and relatively larger when patient health needs are less critical and calls are less urgent. Our next hypothesis follows.

Hypothesis (H2): *Differences in EMS service provision between private and public insurance patients decrease when emergency calls are urgent and patient health needs overshadow patient ability to pay.*

2.4 | Financial Need and Opportunity Cost Increases the Salience of the Financial Objective

While patient health needs should increase the relative strength of the health objective compared to financial incentives from patient ability to pay, there are also important situations where the relative strength of financial incentives will likely overshadow the health objective. In such cases we expect care disparities to increase based on patient ability to pay, as EMS personnel spend more time with and perform more procedures for higher-paying patients, relative to lower-paying patients.

The first driver of relatively stronger financial incentives, compared to the health objective, is opportunity cost. EMS agencies benefit the most financially from transporting private insurance patients, followed by Medicare and then Medicaid patients. Therefore, everything else being equal, agencies prefer to transport patients with private insurance. On busy days, the opportunity cost of serving a low ability to pay patient is relatively higher than on slow days, as the probability of another higher-paying patient needing emergency care in the near future in the unit's service area is higher. For instance, if the unit responds to a Medicaid patient on a busy day, and spends significant time treating and transporting them, they may consequently lose out on the opportunity of responding to the next potentially higher-paying call from a patient with private insurance or Medicare. On busy days, the time between patient calls decreases, but the average time required to treat and transport a patient stays about the same. Thus, the opportunity cost is significantly higher on busy days when treating Medicaid patients. When units are not free to respond to calls on busy days, municipalities often have contracts with outside agencies (Horwitz & McGahan, 2019) or with private companies to fill this needs. EMS units consequently have stronger financial incentives to drop off lower paying patients quicker on busy days, which then allows them increased availability to respond to potential calls from future higher-paying patients thereby capturing more value for their agency. On busy days we consequently expect care disparities to increase between patients with low and high ability to pay, compared to less busy days. This leads to our third hypothesis.

Hypothesis (H3): *Differences in EMS service provision between private and public insurance patients increase on busy days, when the opportunity cost of serving a lower-paying public insurance patient is relatively high.*

Finally, an agency's recent financial situation should influence the relative strength of financial incentives on emergency calls, as it changes the strength of the organization-level financial incentives. If an agency has had many higher-paying private insurance calls in the recent past relative to lower-paying public insurance calls, then the financial pressure on the agency should be relatively lower compared to agencies that have had relatively fewer private insurance calls relative to public insurance calls. As the agency's ratio of private insurance calls increases in the near past this should consequently weaken the financial incentives for EMS professionals to treat patients differently, and instead allow them to focus on patient health outcomes. Conversely, when the ratio of private insurance calls relative to public insurance calls increases, we expect to see professionals act in ways that increase care disparities, as they increase focus on higher ability to pay patients. Our final hypothesis follows:

Hypothesis (H4): *Differences in EMS service provision between private and public insurance patients decrease when the ratio of private insurance to public insurance calls in the recent past increases.*

3. | DATA AND METHODOLOGY

3.1 | Quasi-Random Assignment of EMS Calls to Units

The ideal experiment to address our research question includes randomly assigning insurance type to EMS patients, and then randomly assigning patients in a given service area to EMS units (and their corresponding assigned crews) throughout the day. We could then observe how EMS crews change their on-the-call behavior based on patient ability to pay while avoiding potentially confounding factors stemming from differences in incident location, patient health condition, patient preferences, time of day, or other patient or call-level characteristics.

While this experimental ideal is not feasible, our setting and data approach this ideal. EMS units correspond to a physical EMS vehicle and are nested within EMS agencies that service emergency calls in a stable geographic area. Units are typically staffed by two crew members per shift and staffing needs result in variation in team composition across days. EMS calls are assigned to EMS agencies by 9-1-1 dispatchers. While unit availability and service agreements can influence this assignment,[3] dispatchers do not have information about patient ability to pay when making dispatch decisions, and 9-1-1 dispatch follows a well-defined protocol. Once altered by dispatch, agencies dispatch an available EMS unit to respond to the call. Once on scene, and in conjunction with the patient, EMS crews then decide on a treatment and transport plan, depending on patient condition and needs. Because such encounters are typically rare for patients, and patients lack necessary knowledge to diagnose and treat their health condition, patients often accept the advice and recommendations of EMS personnel.

This dispatch and response process quasi-randomly assigns patients to EMS units throughout a given day. It also quasi-randomly assigns patient insurance type to EMS units. While this approaches the experimental ideal outlined above, insurance type is not randomly assigned to patients, and patients may consequently utilize EMS services differently. Patients with certain types of insurance could live

[3] Some governments, for instance, may contract with private EMS companies to cover less-critical or overload calls. Similarly, governments may agree with other proximate agencies to cover each other's calls when one of their own units is not available (Horwitz & McGahan, 2019)

or work in different places, have different health conditions, ask for different care from treating personnel, or utilize emergency services at different points in the day or on different days of the week. Three aspects of our setting help with this concern. First, we have detailed data that help us to control for these factors. Second, any information related to patient ability to pay should only be revealed after the EMS unit arrives at the scene, which allows us to explore changes in on-the-call behavior depending on patient ability to pay. Finally, the richness of our data allow us to observe which contextual factors lead crews modify their behavior on calls. This increases confidence that ability to pay is indeed driving our results instead of other confounding factors.

Our identification strategy exploits this quasi-random assignment of patients (and their accompanying ability to pay) to EMS unit calls and investigates how EMS crews change their care behavior depending on patient ability to pay, after controlling for confounding factors. We then examine how heterogeneity at the call level, such as with call urgency or unit busyness, influences the main effect. Finally, we provide evidence that helps rule out prominent alternative explanations and that supports our proposed mechanism. Together this allows us to approach causality with our empirical results, although some limitations remain.

3.2 | Data

Our dataset originates from the National Emergency Medical Services Information System (NEMSIS). NEMSIS is a national database that stores standardized EMS call-level data for US states and territories. NEMSIS also provides a universal standard for classifying and collecting patient and call data and has been adopted by EMS agencies throughout the United States. The national NEMSIS database includes yearly call-level data on EMS agencies in 49 states and US territories. Our final sample consists of 12,710,203 observations from 4,831 agencies and 41,237 units in 31 states. To arrive at this final sample, we restricted the data in a few important ways. First, we dropped states with inconsistent reporting across years, defined as deviating in the number of calls reported across years by more than one standard deviation.[4] Second, we retain only 9-1-1 calls for which an EMS unit was dispatched and for which a patient transport occurred. Third, we drop observations without unit-level identifiers, agency identifiers, where the call time reported was zero, and calls without a recorded primary method of payment. Primary method of payment (i.e., insurance) was provided in 34.5% of cases.[5] Fourth, we restrict our sample to agencies with five or more calls per year and to units with more than one call per year. Finally, we drop one outlier agency with significantly higher daily call numbers than the next largest agency, as it appears infeasible for the units to respond to the numbers of calls reported.

We believe that the above restrictions create a conservative sample for study. However, to ensure that our results are not simply an artifact of these restriction choices we reran our main models on the entire dataset, as well as on additional larger subsamples. In all cases our results replicate and the estimates are qualitatively similar, suggesting that sampling choices are not driving our results. We discuss these additional robustness checks later in the paper and provide all supplemental tables in the appendix.

3.3 | Variables

3.3.1 | Dependent Variables. Our primary dependent variables are total *number of procedures performed (procedures)* and EMS *time spent with patient (time)*. We measure the number of procedures by counting the reported medical procedures performed by EMS personnel on the patient during the call. Time with patient is measured as the total minutes EMS personnel spent with a patient, from initial contact

[4] To better identify inconsistent state-level reporting, we collected data from NEMSIS for years 2010 and 2011. These were early years in the collection of data, so we use these data to identify states that are consistently reporting data across years.

[5] Descriptive statistics comparing calls for which insurance was reported compared to calls for which insurance was not reported reveal no significant differences between these two groups. method of payment includes multiple categories, including self-pay (~16% of observations), workers compensation (~0.5%), uncommon types of government-provided insurance (~1%), and non-billed calls (~1.7%), in this paper we only focus on Medicaid (18.03%), Medicare (34.93%) and private insurance (27.73%) calls.

at the scene until final drop-off at the medical facility. We winsorize both variables at the 99th percentile to mitigate effects from outliers and also use a natural log transformation (log + 1). Importantly, we note that while these variables measure key characteristics of EMS care, and allow insight into care equity, they do not necessarily correspond directly to final patient health outcomes. Thus, we cannot say if more procedures or spending additional time with a patient is preferred to the opposite.

3.3.2 | Independent and Moderating Variables. Our primary independent variables are dummies for patient payment method: *Private insurance, Medicare, or Medicaid.* The NEMSIS data include the primary payment method for each call, but do not include information on secondary insurance or total billed or paid amounts. The reimbursement rate of Medicaid for EMS calls is typically the lowest, followed by Medicare and then private insurance (CMS 2019; NEMSAC 2016). Our discussions with EMS personnel revealed that this is common knowledge. Medicaid is used as the omitted baseline category in our analyses.

In addition to these main independent variables, we use moderating interaction variables to establish evidence consistent with our mechanism and subsequent hypotheses. We focus on three moderating variables. The first is *call urgency*, which is a dummy variable that is equal to 1 if lights and sirens are used by the EMS unit leaving the scene en route to the hospital and 0 otherwise. We expect call urgency to weaken the EMS crew's economic incentives and strengthen the crew's focus on patient wellbeing. The second variable is *unit busyness*. This is measured as the log of unit transport calls per day. On busy days the opportunity cost of serving a low ability to pay patient is higher, which strengthens the economic incentives for the EMS crew. The final variable is the *three-month moving average private insurance call ratio by agency (3MMA).* This variable is measured as the percentage of calls an agency has received in the past three months that are paid by private insurance. A higher percentage suggests that the agency has serviced more high ability to pay patients compared to a lower percentage.

We expect that a lower percentage should increase economic incentives for EMS crews, as patients in the recent past have reimbursed the agency less than when the percentage is higher.

3.3.3 | Control Variables. The richness of our data allow us to include many important control variables. We use three categories of controls in our main models: time controls, patient controls, and call-specific controls. For time controls, we include dummies for the call hour of day, day of week, month of year, and year. This accounts for time effects that might impact call outcomes including seasonal effects, weather differences, traffic patterns, weekday vs. weekend differences, and patients' tendencies of utilizing 9-1-1 at different times. At the patient-level we control for patient age, race, and gender. These variables help account for discrimination and subconscious biases that might influence care by EMS personnel as well as for patient health conditions related to gender or age. At the call level we control for (1) the time taken by EMS personnel to reach the scene, which helps control for distance and traffic at time of call, (2) the time taken by EMS personnel at the scene to reach the patient, which controls for issues encountered at the scene, (3) patient condition using primary health impression dummies (e.g., cardiac arrest, stroke, trauma), (4) total care barriers encountered (e.g., language, scene safety, obesity, uncooperative patient, emotional distress) to control for call complications that may influence crew care decisions and ability to deliver care, and (5) reason for choosing drop-off destination (e.g., patient choice, closest destination, diversion) to control for hospital diversions and patient heterogeneity in care requests. These controls reduce concerns about omitted variable bias, as type of insurance may not be random to patient conditions, locations, demographics, or treatment preferences.[6]

3.3.4| Specification

[6] Detailed descriptions for each variable can be found at NEMSIS.org.

Our model estimates the within EMS unit (i.e. ambulance and assigned crew) change in care decisions given a change in patient ability to pay through insurance. We use the following fixed-effects specification to identify the impact of patient payment method on EMS call outcomes:

$$Log(Y_{ijt}) = a_0 + \beta_1 * Medicare_{it} + \beta_2 * Private_{it} + \beta_3 * X_{ijt} + \eta_j + \gamma_t + \varepsilon_{ijt} \qquad (1)$$

where Y_{ijt} is our dependent variable, either patient *procedures* or patient *time,* for EMS call *i* performed by unit *j* at time *t*. $Medicare_{it}$ and $Private_{it}$ are the independent variable indicators for patient insurance type (Medicaid is the omitted baseline) for a given call *i*. X_{ijt} are patient and call-level control variables, ηj are EMS unit fixed effects, γt are hour, day, week, and year time dummies as described above, and ε_{ijt} the error term. In the interacted models we include interactions between insurance types, *Medicare* and *private,* and the moderator variables *lights and sirens,* the log of *unit calls per day,* and *three-month moving average private insurance call ratio by agency (3MMA).* The specification is estimated using OLS with errors clustered at the agency level. Because unit fixed effects are included, the effects are interpreted as the within-EMS unit change in care behaviors given a different patient insurance payment method, controlling for observables. The unit fixed effects should address unit heterogeneity that might influence our dependent variable, such as unit skill level, ability to deduce patient ability to pay (or insurance type), tendency to act against lower paying patients, etc..

Importantly, while patient insurance payment method should be quasi-randomly assigned to an EMS units' calls throughout the day, it may not be entirely exogenous to patient or call characteristics. This is suggested in Figures A1-A3 (appendix). These figures suggest that calls may not be randomly assigned throughout the day or throughout the week within our entire sample based on patient insurance type and that patient conditions may not be randomly distributed among different insurance types. Unit fixed effects, in conjunction with our many control variables described earlier, should reduce endogeneity concerns, selection issues, and biases from omitted variables. However, to rule out alternative explanations and to provide further evidence in favor of our proposed mechanism we perform many robustness checks. These checks decrease concerns that differences in patient characteristics, location, time, or health are driving our results.

4. | RESULTS

4.1 | Patient Ability to Pay Influences Care Given

Table 1 provides descriptive statistics for the relevant dependent, independent, and control variables, broken out by insurance type. Table 2 presents a correlation matrix for our main variables. The mean time with patient for private insurance, Medicare and Medicare is 29.84, 30.63 and 27.48 minutes, respective; while total number of procedures is 1.77, 1.83, and 1.47. The only major differences along controls are related to race and gender. Medicaid patients are generally younger – mean of 42.88 years (compared to 53.93 for private insurance and 72.72 for Medicare) and more likely to be a minority – 46%, (compared to 26% for private insurance and 22% for Medicaid). Figures 1 and 2 show the raw distributions of our data for the dependent variables.

******INSERT TABLES 1 AND 2 HERE******

Our main results are found in Table 3. The fully controlled models, presented in Columns 7 and 8, show that private insurance patients receive more procedures and have longer call times than publicly insured (Medicare and Medicaid) patients. Patients with private insurance have 4.6% more procedures performed and 5.1% longer call times than patients with Medicaid. Medicare patients have 1.5% more procedures[7] and 3.9% longer call times than Medicaid patients. In both cases, the coefficients for private insurance are significantly larger than those for Medicare and Medicaid (Wald Tests $p < 0.001$). These results suggest patient payment method influences EMS personnel behavior and consequently care equity in practically significant ways. EMS units perform more procedures and spend more time with "higher" paying patients on average, which generate larger agency revenues. Together these results provide support for Hypothesis 1.

[7] Poisson fixed effect results, using the untransformed number of total procedures, are found in Table A1 (appendix).

******INSERT TABLE 3 HERE******

4.2 | Salience of the Health Organizational-Level Objective on a Call Influences Care

Table 4 provides results for interaction models that investigate how EMS care changes when the social health objective of the agency is more salient during the call. A dummy for lights and sirens transport from the scene functions as a proxy for call urgency in these models. Urgency is driven by patient health needs. The base results in columns 1 and 2 suggest that the number of procedures increases by 9.2% and time with patient decreases by 3.2% for urgent calls. Columns 3 and 4 provide results by method of payment. Column 3 shows that Medicare patients receive more procedures when lights and sirens are used, compared to Medicaid patients, while private insurance patients experience no change. Thus, the differences between Medicare and private insurance are lessened with call urgency from patient health needs. Surprisingly, the Medicaid group appears to persistently receive fewer procedures than patients with Medicare or private insurance, even for urgent calls.

The time with patient results are presented in Column 4. These results suggest that while call times decrease for both Medicare and private insurance patients when calls are urgent, the drops are 2.5 percentage points larger for patients paying with Medicare or private insurance. Thus, while call times are typically longer overall for Medicare (4.4%) and Private insurance (5.6%) compared to Medicaid, urgent conditions reduce differences to only 1.9% and 3.1% respectively

******INSERT TABLE 4 HERE******

Subsample models for the 14 most common patient conditions (covering 96% of cases in our sample) provide further insights. These results are shown in Figure 3 (a and b) and suggest that time with patient and number of procedures converge across payment methods for more urgent calls and diverge as urgency decreases. When divergence occurs patients with private insurance and Medicare typically have more procedures and longer call times. These results suggest that EMS personnel respond to economic incentives more when calls are less urgent. Stated differently, they prioritize the social health objective of the organization when patient health needs require it. These results provide support for Hypothesis 2.

******INSERT FIGURE 3(a/b) HERE******

4.3 | Salience of the Financial Organizational-Level Objective on a Call Influences Care

Table 5 provides results for interaction models that investigate how EMS care changes when the financial objective of the agency is more salient during the call. In these models daily call volume proxies for unit busyness and highlights call opportunity cost, which is highest for Medicaid calls. Columns 1 and 2 indicate that on busy days all patients are dropped off sooner than on non-busy days. However, the interaction models in Columns 3 and 4 suggest an important role for insurance—Medicaid patients receive fewer procedures and are dropped off sooner than privately insured patients as busyness increases. These results suggest that units provide fewer resources to Medicaid patients on busy days, potentially in anticipation of higher-paying future calls from private or Medicare patients. These findings provide support for Hypothesis 3.

******INSERT TABLE 5 HERE******

If private insurance helps agencies recoup losses from treating and transporting public insurance patients, then we also expect to see differences based on the agency's historic private to total call ratio. Having a higher private call ratio in the recent past should alleviate agency economic pressures. The results, presented in Table 6, suggest that as the *three-month moving average private insurance call ratio by agency (3MMA)* increases EMS units spend more time with and perform more procedures for Medicaid patients, which consequently reduces care inequity. Stated differently, the gaps in care given are reduces when agencies have responded to more calls for private insurance patients in the recent past. This again suggests care disparities are driven by the saliency of agency financial pressures in the minds of EMS crew members. This provides support for Hypothesis 4

******INSERT TABLE 6 HERE******

We lastly examine whether our main results vary by differences in organization size and type. Organizations may differ in the personnel they employ and in the funding they receive. First, we examine the effects of agency size, measured by the number of units (median=4 units). The results, presented in Table A2 (appendix), suggest differences based on payment method are more prominent in larger agencies. Second, we examine if organization type influences our main results. Figure A4 (a and b) (appendix) shows our main model results by organization type subsamples. It suggests that care disparities are prevalent across organization types.

5. | ROBUSTNESS AND ADDITIONAL ANALYSES

5.1 | Ruling out Alternative Explanations

While our main results hold across multiple controls and with unit fixed effects, we perform additional robustness checks to rule out alternative explanations. First, it is possible that Medicare or Medicaid patients use EMS differently, perhaps delaying calling 9-1-1 for a given health condition, which influences call urgency and subsequently care. To address this concern, we conducted four subsample analyses, found in Table A3 (appendix): (1) only patients who are eventually admitted to the hospital; (2) only lights and sirens calls; (3) only calls during the night (10:00 PM-6:00 AM); and (4) only calls between midnight and 1:00 AM. The first two subsamples should include patients with more similar health conditions across insurance types than those in our main sample. The last two subsamples should reflect calls that are "unplanned" and thus reduces unobserved differences in patient characteristics. The results for these subsample analyses are similar to our main models. Additionally, we reran our main models with more granular patient condition dummies, which are used for final billing.[8] While missing codes reduced our sample size, the results (Table A4 in the appendix) are similar.

[8] The main model primary impression dummies capture EMS unit impression of patient health condition. Patient condition codes provide an ex post evaluation of the patient's condition.

Second, we test for potential selection issues in the determination of our final sample. To do this we reran our main results on a larger collected dataset from NEMSIS with additional states and years,[9] as well as on the full sample of 9-1-1 calls regardless of patient transport. The results, shown in Tables A5 and A6 (appendix), are again similar, suggesting sample selection is not driving our results.

Third, it could be that dual insurance (e.g., having Medicare and private insurance) is influencing our results. To test this, we omit from our analysis patients over 65—those who are likely covered by Medicare—who specified private insurance as their primary insurance. The results, shown in Table A7 (appendix), are again similar.

Fourth, our main results could be driven by patient demographics, especially because Medicare is only for older patients. We consequently estimate a subsample for patients who are 65 or older. Medicare sometimes requires sizable premium payments, and around 20% of Medicare patients can be dual-eligible for Medicaid and Medicare (Schultz 2020), which effectively covers most medical costs. The results, shown in Table A8 (appendix), are again similar to our main results.

Fifth, racial discrimination could be influencing our results. Healthcare studies have found that racial discrimination drives care inequity (Hanchate et al. 2019; Nelson 2002). While our models control for patient race, we also ran models using a dummy for M*inority* (White=0, Others=1). The results, shown in Table A9 (appendix), suggest minorities receive fewer procedures and less EMS time. The results hold even after controlling for patient payment method. This suggests that EMS personnel have systematic biases during calls, which extend both to race and patient ability to pay. To rule out race effects completely we reran our model on only White patients. The results, found in Table A10, are similar to our main results. Put together, our results indicate that patient ability to pay offers a different pathway to care disparities than racial discrimination that has been examined previously.

[9] We collected additional data for more US states and additional years to confirm that sample selection is not driving our main results. Many of these states and early adoption years only have partial reporting by EMS agencies.

Finally, to provide further evidence towards causality and address concerns about omitted variable bias we conduct an instrumental variable estimation. We instrument for private insurance using *3MMA*, as defined earlier. The historic ratio of private insurance calls at an agency should be correlated with patient payment method on the next call but should not predict on-call performance (see Columns 1 and 2 in Table 5). Table A11 (appendix) presents the instrumental variable estimation. The second stage results, in Columns 2 and 3, are again consistent with our main results.

5.2 | Remaining Limitations

While the above analyses have allowed us to rule out many important alternative explanations, limitations remain. First, we cannot observe the exact incident location and distance to ER. Due to confidentiality and identification concerns – such data are not made available. However, considering that EMS agencies serve a fixed pre-established area and their location is typically permanent – using response and transport times as proxies for distance while controlling for any barriers provides an appropriate and sufficiently precise estimate for distance travelled. Second, we are unable to account for heterogeneity in reimbursement rates or funding structures across EMS agencies. While our fixed effects specifications should account for unobservable time invariant differences within units (e.g., units service areas, funding structure, level of training, etc.), there could be additional time-variant factors influencing our results. Relatedly, we treat all states similarly based on the average decreasing reimbursement rates across different types of insurance (private, Medicare, and Medicaid), when in actuality these rates may differ to some extent across states. Finally, we are not able to directly measure initial or final patient condition, or EMS units' effort in calls. While our controls, subsample analyses, and unit fixed effects help alleviate these concerns and suggest that patient ability to pay impacts care, it remains unclear how this ultimately influences patient health outcomes. Future research should examine the magnitude of the health impact for each patient based on ability to pay.

6. | DISCUSSION AND CONCLUSIONS

EMS agencies are generally underfunded and consequently rely on self-generated revenues (pay-for-service) to remain viable. At the same time, however, they are required by law to serve patients in need regardless of their ability to pay. EMS personnel, who enter the profession with the social mission of saving lives, are typically compensated by fixed salary. This setting creates powerful incentive for agencies to prefer patients with private insurance, but it is unclear what the impact on EMS crews will be absent direct economic incentives. Our results indicate EMS crews actively engage in balancing the conflicting trade-offs between social and financial organizational-level objectives and dynamically adjust their behaviors on calls, depending on context, to simultaneously maximize on both dimensions. Robustness checks, including instrumental variable analysis, cast doubt on alternative explanations driving these results including discrimination, location, traffic patterns, health conditions, or patient preferences.

Our research makes several contributions to the literatures on multiple objective organizations, incentives, and healthcare. First, we provide important insights to managing hybrid organizations that simultaneously pursue multiple goals: In our case a prosocial health objective and financial viability. Studies have found that concurrent pursuit of several, and sometimes conflicting, objectives are evident in public firms, universities, and small firms alike. However, the current literature on goal multiplicity mainly examines the phenomena from the perspectives of organizations and top management (e.g., Battilana & Lee 2014; Obloj & Sengul 2020; Gaba & Greve 2019), with the prescriptions to deal with these problems existing at the organizational or managerial levels. Our study sheds light on the behaviors of frontline employees who have a significant amount of discretion in their work, and show they dynamically balance conflicting organizational goals in a way that organizations and managers are unable to achieve. This contributes to a small but emerging literature on multiple objective (Gaba & Greve, 2019; Hu & Bettis, 2018; McCann & Vroom, 2014) and dual-purpose organizations (see Battilana & Lee, 2014 for a review).

These findings likewise contribute to our understanding of incentives in organizations with social objectives. While organizational studies suggest that organizational-level incentives can spill over into individual-level decisions even when individual financial incentives are absent (e.g., Batson 1994, Deci & Ryan 1985, Grant et al. 2008, Prendergast, 2008), significantly less is known about how indirect incentives affect healthcare professionals when a prosocial health mission exists. In the context of EMS personnel, who are typically salaried and have limited direct benefit from the patients they serve, we find that they do respond to financial challenges faced by their agencies, but still cater to patient wellbeing whenever the situations require. Our results consequently highlight the importance of indirect incentives in multiple objective organizations, but also show that these incentives can be influenced by the other objectives simultaneously pursued by the firm.

Finally, our results contribute to the literatures on EMS performance and healthcare outcomes, which have primarily focused on optimal ambulance location and dispatching decisions (e.g., Deo & Gurvich 2011, Keskinocak & Savva 2020, Kamali et. al 2019), response times (e.g., Alanis et al. 2013, Budge et al. 2009, 2010), efficiencies in emergency departments (e.g., Batt, Terwiesch 2017, He et. al 2019, Rogg et al. 2017, Song et al. 2015), and medical interventions. Our results suggest that EMS personnel are responsive to their organization's financial incentives and this can lead to care disparities depending on patient ability to pay. Health inequity is a critical challenge for the US healthcare system generally. Our work indicates that these healthcare disparities may be driven in part by economic incentives of the organization, which spill over to its workforce even in the absence of clear financial incentives.

6.1 | Managerial and Policy Implications

Although EMS personnel are intrinsically motivated to improve patient health, we have shown that powerful organizational-level incentives can influence individual level behaviors even without direct financial benefits. This raises important managerial policy challenges as it pertains to managing hybrid healthcare organizations and maintaining healthcare equity.

One potential solution for addressing the dark side of incentives in healthcare, which has been adopted by various health organizations including the Mayo Clinic and the Kaiser group, is to remove direct performance pay and instead use salary-based remuneration. However, our results highlight that even such a system is not problem-free, as we have shown that indirect incentives can still significantly influence care decisions. Given that salary structures may not remove discrepancies in care under conditions of strong organizational level incentives, managers must explore other non-pay options for minimizing care inequities.

More challenging in healthcare organizations relative to a typical hybrid organization is that it is impractical or even unethical to set financial goals for their employees. However, the tension between social objective and financial viability does not disappear by hiding it at the background. It may consequently be more helpful to bring these issues into the open and engage employees by actively discussing the trade-offs between creating social and economic value (Battilana et al., 2015). It is consequently crucial to focus on the root causes of organizational challenges from multiple objectives, and how the (lack of) training, organizational culture, and incentive systems might contribute to or alleviate these challenges.

Leaders should also have a strategy for managing human resources when given autonomy. Employees tend to be more successful when they are able to identify with both the economic and social objective. Research has argued that hybrid individuals, who have training or experience with both business or social value concepts, can connect with customers or stakeholders from both perspectives (Battilana & Lee 2014). Hybrid employees are well-suited for managerial and coordination position to work in organizations with dual purposes. Other studies have also examined the possibility of matching on preferences in the absence of economic incentives (Prendergast, 2008).

Ultimately curbing care disparities entirely may require changing current reimbursement policies. Financial viability is a necessary (although not sufficient) condition for agencies to continue to stay operational. Better informed policies together with training, monitoring (e.g., Staats et al. 2016), and improved care protocols (e.g., Ganju et al. 2020) are potentially important to resolving care differences based on patient ability to pay. Ultimately, however, lasting changes may require a shift in national policy, especially as it relates to the manner in which EMS agencies are funded via public and private insurance. Removing financial uncertainty (e.g., at or below cost reimbursement for Medicaid and Medicare or more robust public funding) could potentially minimize organizational-level incentives to recoup losses from patients with high ability to pay.

For dual-objective organizations, meeting financial expectations sometimes means violating social expectations (Battilana et al., 2020; Hahn et al., 2010). If financial pressures continue to increase, the possible of "mission drift" (i.e., relegating the social goal of the organization) becomes a real possibility (Grimes et al., 2019). Our research shows that these tradeoffs happen not only at the managerial or organizational level, but also at the employee level. Our paper suggests that managers and policy makers must not only consider and manage incentives for desired behaviors, and their unintended consequences (e.g., Kerr 1975), but also consider how neglected indirect incentives can potentially cause unintended effects on intrinsically-motivated employees.

We acknowledge that there is no simple solution that could easily maximize all organizational objectives, but our results indicate that firms, managers and employees may learn to recognize and manage multiple objectives and tradeoffs over time. Recent research has highlighted the unique importance of hybrid organizations that combine multiple forms for organizational innovation and institutional change (Battilana et al., 2015; Padgett & Powell, 2012). We hope our study will invite additional future investigations into possible solutions.

7. | REFERENCES (*NOT YET UPDATED ENTIRELY*)

Asch, D. A., Troxel, A. B., Stewart, W. F., Sequist, T. D., Jones, J. B., Hirsch, A. G., ... & Frasch, A. B. (2015). Effect of financial incentives to physicians, patients, or both on lipid levels: a randomized clinical trial. *JAMA*, *314*(18), 1926-1935.

Augustine, J. J. (2014). Emergency medical services arrivals, admission rates to the emergency department analyzed. *ACEP Now*, *33*(12), 1-4.

Battilana, J., & Lee, M. (2014). Advancing research on hybrid organizing–Insights from the study of social enterprises. *Academy of Management Annals*, *8*(1), 397-441.

Battilana, J., Obloj, T., Pache, A. C., & Sengul, M. (2020). Beyond Shareholder Value Maximization: Accounting for Financial/Social Tradeoffs in Dual-Purpose Companies. *Academy of Management Review*

Battilana, J., Sengul, M., Pache, A. C., & Model, J. (2015). Harnessing productive tensions in hybrid organizations: The case of work integration social enterprises. *Academy of Management Journal*, *58*(6), 1658-1685.

Berwick, D. M., Nolan, T. W., & Whittington, J. (2008). The triple aim: care, health, and cost. *Health Affairs, 27*(3), 759-769.

Besley, T., & Ghatak, M. (2018). Prosocial motivation and incentives. *Annual Review of Economics*, 10, 411-438.

Chetty, R., Stepner, M., Abraham, S., Lin, S., Scuderi, B., Turner, N., ... & Cutler, D. (2016). The association between income and life expectancy in the United States, 2001-2014. *JAMA*, *315*(16), 1750-1766.

Clemens, J., & Gottlieb, J. D. (2014). Do physicians' financial incentives affect medical treatment and patient health? *American Economic Review*, *104*(4), 1320-49.

CMS. (2019). *Medicare's ground ambulance data collection system: Sampling and instrument considerations and recommendations*. Baltimore, MD: CMS..

CMS. (2020). *Emergency Medical Treatment & Labor Act (EMTALA)*. Retrieved March 11, 2020 from https://www.cms.gov/Regulations-and-Guidance/Legislation/EMTALA.

Cyert, R. M., & March, J. G. (1963). *A behavioral theory of the firm*. Englewood Cliffs, NJ: Prentice-Hall.

Dai, T., & Tayur, S. R. (2019). Healthcare operations management: A snapshot of emerging research. *Manufacturing & Service Operations Management.*

Delgado, M. K., Yokell, M. A., Staudenmayer, K. L., Spain, D. A., Hernandez-Boussard, T., & Wang, N. E. (2014). Factors associated with the disposition of severely injured patients initially seen at non–trauma center emergency departments: disparities by insurance status. *JAMA Surgery*, *149*(5), 422-430.

Doherty, B., Haugh, H., & Lyon, F. (2014). Social enterprises as hybrid organizations: A review and research agenda. *International Journal of Management Reviews*, *16*(4), 417-436.

Ethiraj, S. K., & Levinthal, D. (2009). Hoping for A to Z while rewarding only A: Complex organizations and multiple goals. *Organization Science*, 20(1), 4-21.

Flodgren, G., O'Brien, M. A., Parmelli, E., & Grimshaw, J. M. (2019). Local opinion leaders: effects on professional practice and healthcare outcomes. *Cochrane Database of Systematic Reviews*, 6. Retrieved from https://www.cochranelibrary.com/cdsr/doi/10.1002/14651858.CD000125.pub5/full

Gaba, V., & Greve, H. R. (2019). Safe or profitable? The pursuit of conflicting goals. *Organization Science*, *30*(4), 647-667.

Ganju, K. K., Atasoy, H., McCullough, J., & Greenwood, B. (2020). The role of decision support systems in attenuating racial biases in healthcare delivery. *Management Science*, *66*(11), 5171-5181.

GAO. (2007). *Ambulance providers: Costs and expected Medicare margins vary greatly*. Washington, DC: GAO.
GAO. (2012). *Costs and Medicare margins varied widely: Transports of beneficiaries have increased*. Washington, DC: GAO.
Gaffney, A., & McCormick, D. (2017). The Affordable Care Act: Implications for health-care equity. *The Lancet*, *389*(10077), 1442-1452.
Grimes, M. G., Williams, T. A., & Zhao, E. Y. (2019). Anchors aweigh: The sources, variety, and challenges of mission drift. *Academy of Management Review*, *44*(4), 819-845.
Gruber, J., Kim, J., & Mayzlin, D. (1999). Physician fees and procedure intensity: the case of cesarean delivery. *Journal of Health Economics*, *18*(4), 473-490.
Gruber, J., & Owings, M. (1994). Physician financial incentives and cesarean section delivery. *The RAND Journal of Economics, 27*(1), 99-123.
Hanchate, A. D., Paasche-Orlow, M. K., Baker, W. E., Lin, M. Y., Banerjee, S., & Feldman, J. (2019). Association of race/ethnicity with emergency department destination of Emergency Medical Services transport. *JAMA Network Open*, 2(9), 1-13.
Hayes, S. N., Noseworthy, J. H., & Farrugia, G. (2020). A structured compensation plan results in equitable physician compensation. *Mayo Clinic Proceedings*, 95(1), 35–43.
Holmén, J., Herlitz, J., Ricksten, S. E., Strömsöe, A., Hagberg, E., Axelsson, C., & Rawshani, A. (2020). Shortening Ambulance Response Time Increases Survival in Out‐of‐Hospital Cardiac Arrest. *Journal of the American Heart Association, 9*(21), 1-24.
Horwitz, J. R., & McGahan, A. M. (2019). Collaborating to manage performance trade‐offs: How fire departments preserve life and save property. *Strategic Management Journal*, *40*(3), 408-431.
Hu, S., & Bettis, R. A. (2018). Multiple organization goals with feedback from shared technological task environments. *Organization Science*, *29*(5), 873-889.
Joseph, J., Klingebiel, R., & Wilson, A. J. (2016). Organizational structure and performance feedback: Centralization, aspirations, and termination decisions. *Organization Science*, *27*(5), 1065-1083.
KC, D. S., Scholtes, S., & Terwiesch, C. (2020). Empirical research in healthcare operations: Past research, present understanding, and future opportunities. *Manufacturing & Service Operations Management*, *22*(1), 73-83.
Larkin, I., Ang, D., Steinhart, J., Chao, M., Patterson, M., Sah, S., ... & Loewenstein, G. (2017). Association between academic medical center pharmaceutical detailing policies and physician prescribing. *JAMA*, *317*(17), 1785-1795.
Lindenauer, P. K., Remus, D., Roman, S., Rothberg, M. B., Benjamin, E. M., Ma, A., & Bratzler, D. W. (2007). Public reporting and pay for performance in hospital quality improvement. *New England Journal of Medicine*, *356*(5), 486-496.
Lipsky, M. (2010). *Street-level bureaucracy: Dilemmas of the individual in public service*. New York, NY: Russell Sage Foundation.
Margolis, J. D., & Walsh, J. P. (2003). Misery loves companies: Rethinking social initiatives by business. *Administrative Science Quarterly*, 48(2), 268–305.
Munjal, K. G., Margolis, G. S., & Kellermann, A. L. (2019). Realignment of EMS reimbursement policy: New hope for patient-centered out-of-hospital care. *JAMA*, *322*(4), 303-304.
Navathe, A. S., Emanuel, E. J., Bond, A., Linn, K., Caldarella, K., Troxel, A., ... & Bernheim, S. (2019). Association between the implementation of a population-based primary care payment system and achievement on quality measures in Hawaii. *JAMA*, *322*(1), 57-68.

Neely, K. W., Drake, M. E., Moorhead, J. C., Schmidt, T. A., Skeen, D. T., & Wilson, E. A. (1997). Multiple options and unique pathways: a new direction for EMS? *Annals of Emergency Medicine*, *30*(6), 797-799.

Nelson, A. (2002). Unequal treatment: confronting racial and ethnic disparities in health care. *Journal of the National Medical Association*, *94*(8), 666-668.

NEMSAC. (2016). *EMS funding and reimbursement*. Washington, DC: NEMSAC.

Obloj. T., & Sengul, M. (2020) What do multiple objectives really mean for performance? Empirical evidence from the French manufacturing sector. *Strategic Management Journal*.

O'Keeffe, C., Nicholl, J., Turner, J., & Goodacre, S. (2011). Role of ambulance response times in the survival of patients with out-of-hospital cardiac arrest. *Emergency Medicine Journal*, *28*(8), 703-706.

Olshaker, J. S., & Rathlev, N. K. (2006). Emergency department overcrowding and ambulance diversion: the impact and potential solutions of extended boarding of admitted patients in the emergency department. *The Journal of Emergency Medicine*, *30*(3), 351-356.

O'Reilly, C. A., & Tushman, M. L. (2013). Organizational ambidexterity: Past, present, and future. *Academy of Management Perspectives*, *27*(4), 324-338.

Pache, A. C., & Santos, F. (2013). Inside the hybrid organization: Selective coupling as a response to competing institutional logics. *Academy of Management Journal*, *56*(4), 972-1001.

Petersen, L. A., Woodard, L. D., Urech, T., Daw, C., & Sookanan, S. (2006). Does pay-for-performance improve the quality of health care? *Annals of Internal Medicine*, *145*(4), 265-272.

Prendergast, C. (2008). Intrinsic motivation and incentives. *American Economic Review*, 98(2), 201-205.

Richardson, L. D., Asplin, B. R., & Lowe, R. A. (2002). Emergency department crowding as a health policy issue: past development, future directions. *Annals of Emergency Medicine*, *40*(4), 388-393.

Roth, A., Tucker, A. L., Venkataraman, S., & Chilingerian, J. (2019). Being on the productivity frontier: identifying "triple aim performance" hospitals. *Production and Operations Management*, *28*(9), 2165-2183.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55(1), 68-78.

Schroeder, S. A. (2007). We can do better—improving the health of the American people. *New England Journal of Medicine, 357*(12), 1221-1228.

Schultz, J. (2020). Can I be enrolled in Medicare and Medicaid at the same time? Medicaresources.org. Retrieved from https://www.medicareresources.org/faqs/can-i-be-enrolled-in-medicare-and-medicaid-at-the-same-time/

Staats, B. R., Dai, H., Hofmann, D., & Milkman, K. L. (2017). Motivating process compliance through individual electronic monitoring: An empirical examination of hand hygiene in healthcare. *Management Science*, *63*(5), 1563-1585.

USBLS. (2020). EMTs and paramedics : Occupational outlook handbook. Retrieved from https://www.bls.gov/ooh/healthcare/emts-and-paramedics.htm

Venkatesh, A. K., Chou, S. C., Li, S. X., Choi, J., Ross, J. S., D'Onofrio, G., ... & Dharmarajan, K. (2019). Association between insurance status and access to hospital care in emergency department disposition. *JAMA Internal Medicine, 179*(5), 686-693.

Webb, E. M., & Mills, A. F. (2019). Incentive–Compatible Prehospital Triage in Emergency Medical Services. *Production and Operations Management*, *28(*9), 2221-2241.

8. | FIGURES AND TABLES

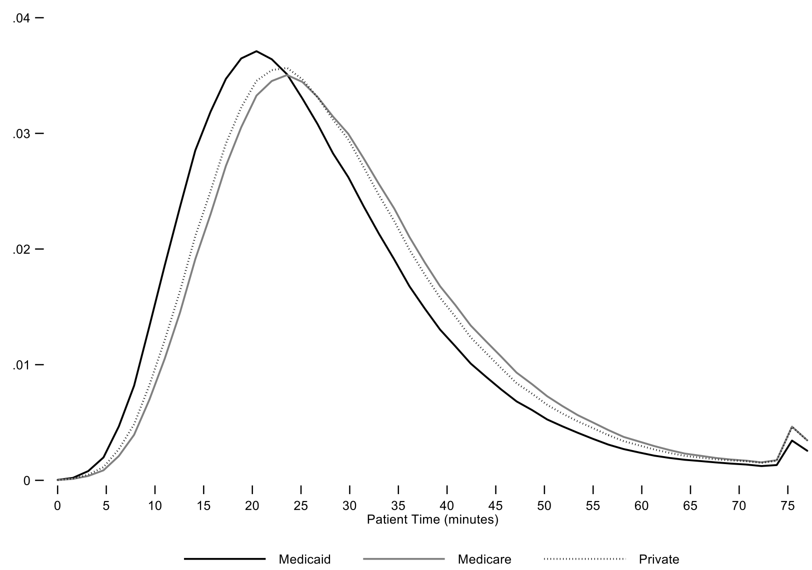


Figure 1. Kernel Density Plot of Raw Data for Time with Patient

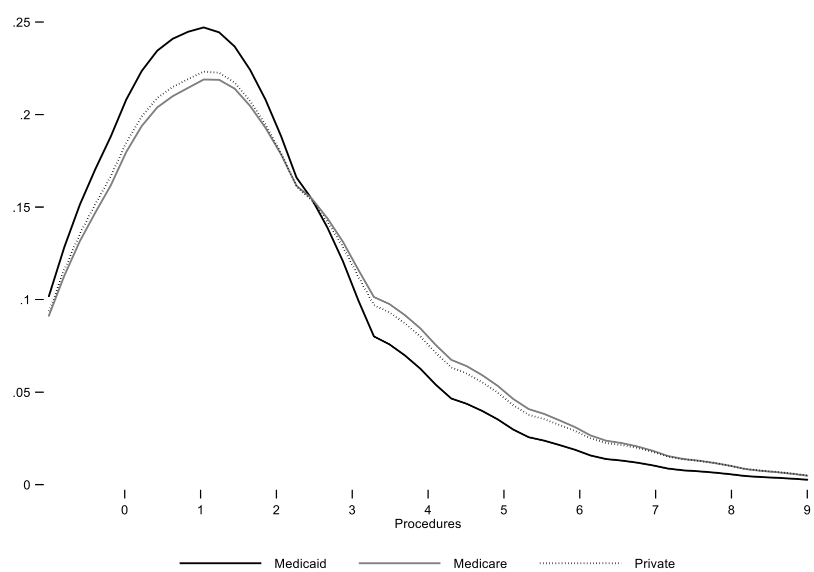


Figure 2. Kernel Density Plot of Raw Data for Number of Procedures Performed

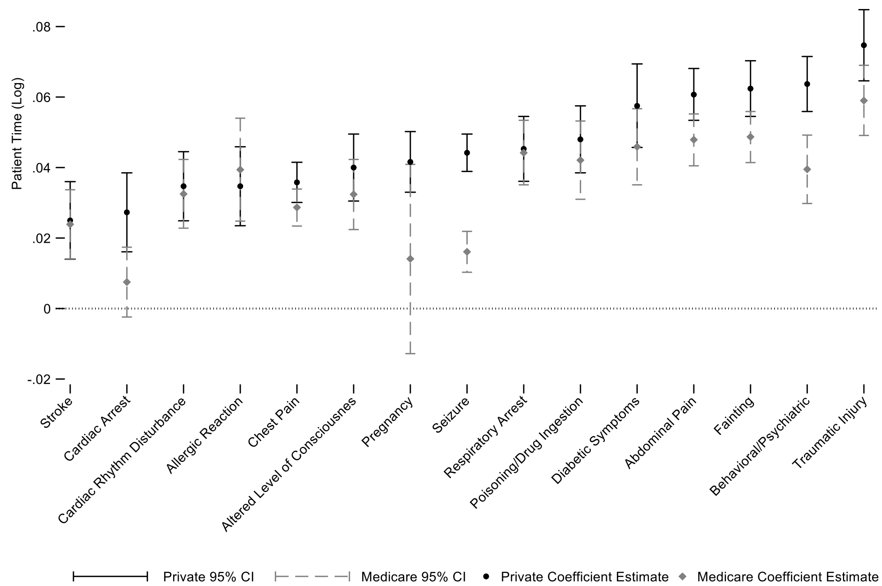


Figure 3a. Time with Patient Disparities Lower for More Critical Health Conditions

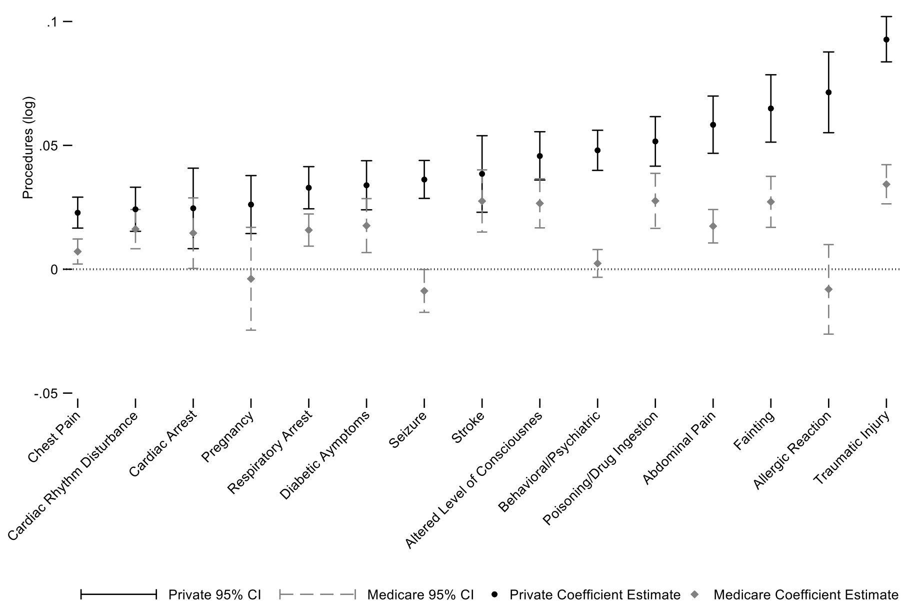


Figure 3b. Procedure Count Disparities Lower for More Critical Health Conditions

Table 1. Sample Descriptive Statistics by Patient Insurance Type

Variable	Count	Mean	SD	Min	Max
Medicaid					
Time with Patient (minutes)	2,657,225	27.48	13.93	1	108
Total Number of Procedures	2,884,262	1.47	1.57	0	8
Hour of Day	2,884,357	12.83	6.60	0	23
Day of Week	2,884,357	2.99	1.97	0	6
Month of Year	2,884,357	6.54	3.41	1	12
Year	2,884,357	2,014.25	1.35	2012	2016
Female	2,878,912	0.57	0.49	0	1
Minority	2,256,778	0.46	0.50	0	1
Age	2,879,890	42.88	20.98	0	120
Total Number of Barriers	2,884,357	0.04	0.21	0	6
Time to Reach Scene (minutes)	2,812,691	7.75	5.58	1	31
Medicare					
Time with Patient (minutes)	5,196,511	30.63	14.31	1	108
Total Number of Procedures	5,645,068	1.83	1.84	0	8
Hour of Day	5,645,310	12.75	6.12	0	23
Day of Week	5,645,310	2.99	1.96	0	6
Month of Year	5,645,310	6.43	3.47	1	12
Year	5,645,310	2,014.06	1.37	2012	2016
Female	5,632,887	0.58	0.49	0	1
Minority	4,879,783	0.22	0.42	0	1
Age	5,635,563	72.74	15.26	0	120
Total Number of Barriers	5,645,310	0.06	0.24	0	8
Time to Reach Scene (minutes)	5,488,289	7.91	5.92	1	31
Private					
Time with Patient (minutes)	3,768,909	29.84	14.30	1	108
Total Number of Procedures	4,180,380	1.77	1.83	0	8
Hour of Day	4,180,536	12.88	6.36	0	23
Day of Week	4,180,536	3.00	1.96	0	6
Month of Year	4,180,536	6.45	3.43	1	12
Year	4,180,536	2014.14	1.39	2012	2016
Female	4,168,088	0.55	0.50	0	1
Minority	3,506,988	0.26	0.44	0	1
Age	4,172,321	53.93	23.19	0	120
Total Number of Barriers	4,180,536	0.04	0.21	0	8
Time to Reach Scene (minutes)	4,055,100	7.59	5.54	1	31

Table 2. Correlation Matrix (N =12,710,203)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Medicaid													
Medicare	-0.484												
Private Insurance	-0.379	-0.626											
Time with Patient	-0.083	0.062	0.009										
Total Number of Procedures	-0.079	0.050	0.018	0.160									
Hour of the Day	0.001	-0.008	0.008	0.021	-0.002								
Day of the Week (Sunday = 0)	-0.002	-0.001	0.003	0.009	-0.001	0.006							
Month of the Year	0.013	-0.008	-0.003	-0.008	0.002	-0.001	-0.004						
Year	0.046	-0.043	0.005	0.004	0.055	-0.005	0.002	-0.028					
Gender (Female = 1)	0.003	0.025	-0.029	0.003	-0.023	0.003	-0.003	-0.002	-0.012				
Minority (White = 0, Other = 1)	0.204	-0.126	-0.043	-0.103	-0.077	-0.019	0.000	0.016	0.030	0.000			
Age	-0.397	0.503	-0.178	0.102	0.074	-0.010	-0.001	-0.013	-0.027	0.062	-0.226		
Total Number of Barriers	-0.019	0.032	-0.016	0.026	0.018	0.002	0.002	0.004	0.007	-0.014	-0.010	0.035	
Time to Reach Scene	-0.002	0.022	-0.022	0.262	-0.026	0.008	0.009	-0.002	0.005	-0.009	-0.016	0.024	0.005

Table 3. Main Effects of Patient Payment Method on Care Disparities

	(1) Log(procedures)	(2) Log(time)	(3) Log(procedures)	(4) Log(time)	(5) Log(procedures)	(6) Log(time)	(7) Log(procedures)	(8) Log(time)
Medicare	0.085	0.116	0.085	0.115	0.033	0.054	0.019	0.040
	(0.005)	(0.006)	(0.005)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Private Insurance	0.098	0.094	0.097	0.093	0.080	0.070	0.061	0.053
	(0.005)	-0.004	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.739	3.237	0.642	3.205	0.614	3.161	0.642	2.858
	(0.004)	(0.004)	(0.014)	(0.008)	(0.016)	(0.011)	(0.024)	(0.015)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Unit Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Time Controls			Y	Y	Y	Y	Y	Y
Patient Controls					Y	Y	Y	Y
Call Controls							Y	Y
N	12,709,710	11,622,645	12,709,710	11,622,645	10,608,836	9,640,674	6,067,231	5,639,533
Adj. R-sq.	0.005	0.012	0.008	0.014	0.018	0.021	0.118	0.096

Notes. Robust standard errors in parentheses clustered by agencies. P-values in square brackets. Time controls include dummies for hour of day, day of week, month, and year. Patient controls include continuous age and dummies for race and gender. Call controls include the numbers of barriers encountered, log (call response time), and dummies for reason for choosing destination and provider impression for type of patient health condition.

Table 4. Call Urgency Moderates Patient Payment Method Care Disparities

	(1) Log(procedures)	(2) Log(time)	(3) Log(procedures)	(4) Log(time)
Lights and Sirens Transport	0.149	-0.017	0.142	0.006
	(0.011)	(0.006)	(0.015)	(0.006)
	[0.000]	[0.002]	[0.000]	[0.261]
Medicare			0.015	0.045
			(0.003)	(0.003)
			[0.000]	[0.000]
Private Insurance			0.060	0.059
			(0.004)	(0.003)
			[0.000]	[0.000]
Medicare × Lights and Sirens			0.015	-0.030
			(0.009)	(0.005)
			[0.086]	[0.000]
Private Insurance × Lights and Sirens			-0.001	-0.031
			(0.009)	(0.004)
			[0.882]	[0.000]
Constant	0.666	2.887	0.634	2.856
	(0.025)	(0.015)	(0.025)	(0.015)
	[0.000]	[0.000]	[0.000]	[0.000]
Unit Fixed Effects	Y	Y	Y	Y
Time Controls	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y
N	5,928,680	5,518,520	5,928,680	5,518,520
Adj. R-sq	0.125	0.095	0.127	0.097

Notes. Robust standard errors in parentheses clustered by agencies. P-values in square brackets. Time controls include dummies for hour of day, day of week, month, and year. Patient controls include continuous age and dummies for race and gender. Call controls include the numbers of barriers encountered, log (call response time) and dummies for reason for choosing destination and provider impression for type of patient health condition. Lights and sirens transport takes the value of 1 if lights and sirens are used transporting a patient from the scene.

Table 5. Unit Busyness Moderates Patient Payment Method Care Disparities

	(1) Log(procedures)	(2) Log(time)	(3) Log(procedures)	(4) Log(time)
Log(Unit Calls per Day)	-0.008	-0.028	-0.014	-0.033
	(0.005)	(0.002)	(0.005)	(0.002)
	[0.102]	[0.000]	[0.009]	[0.000]
Medicaid			-0.049	-0.038
			(0.006)	(0.006)
			[0.000]	[0.000]
Medicare			-0.059	-0.029
			(0.004)	(0.004)
			[0.000]	[0.000]
Medicaid × Log(Unit Calls per Day)			-0.011	-0.013
			(0.006)	(0.006)
			[0.066]	[0.016]
Medicare × Log(Unit Calls per Day)			0.017	0.014
			(0.004)	(0.004)
			[0.000]	[0.000]
Constant	0.687	2.916	0.717	2.946
	(0.024)	(0.015)	(0.024)	(0.015)
	[0.000]	[0.000]	[0.000]	[0.000]
Unit Fixed Effects	Y	Y	Y	Y
Time Controls	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y
N	6,067,231	5,639,533	6,067,231	5,639,533
Adj. R-sq.	0.116	0.094	0.118	0.096

Notes. Robust standard errors in parentheses clustered by agencies. P-values in square brackets. Time controls include dummies for hour of day, day of week, month, and year. Patient controls include continuous age and dummies for race and gender. Call controls include the numbers of barriers encountered, log (call response time) and dummies for reason for choosing destination and provider impression for type of patient health condition. Unit calls per day is the log of the unit's number of transport calls per day.

Table 6. Effects of Private Call Ratio on Procedures Performed and Time with Patient

	(1) Log (procedures)	(2) Log (time)	(3) Log (procedures)	(4) Log (time)
3MMA Private Call Ratio by Agency	0.014	0.003	0.043	0.070
	(0.081)	(0.010)	(0.083)	(0.022)
	[0.859]	[0.738]	[0.603]	[0.001]
Medicare	0.019	0.040	0.014	0.051
	(0.003)	(0.003)	(0.009)	(0.010)
	[0.000]	[0.000]	[0.111]	[0.000]
Private Insurance	0.061	0.053	0.087	0.088
	(0.003)	(0.003)	(0.010)	(0.007)
	[0.000]	[0.000]	[0.000]	[0.000]
Medicare × 3MMA Private Call Ratio by Agency			0.017	-0.042
			(0.027)	(0.028)
			[0.533]	[0.130]
Private Insurance × 3MMA Private Call Ratio by Agency			-0.075	-0.108
			(0.026)	(0.018)
			[0.004]	[0.000]
Constant	0.637	2.857	0.629	2.839
	(0.037)	(0.016)	(0.038)	(0.017)
	[0.000]	[0.000]	[0.000]	[0.000]
Unit FE	Y	Y	Y	Y
Time Controls	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y
N	6,067,231	5,639,533	6,067,231	5,639,533
Adj. R-sq.	0.118	0.096	0.118	0.096

Notes. Robust standard errors in parentheses, clustered at the agency level. P-values in square brackets. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Three Month Moving Average (3MMA) Private Call Ratio by Agency is defined as the mean ratio of private to insurance calls over the past month serviced the agency. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers, logged response time, reason for choosing destination FE, provider primary impressions FE).

Appendix
Supplemental Analyses

Figure A1. Kernel Density Plot of Number of Calls by Hour of the Day by Primary Method of Pay

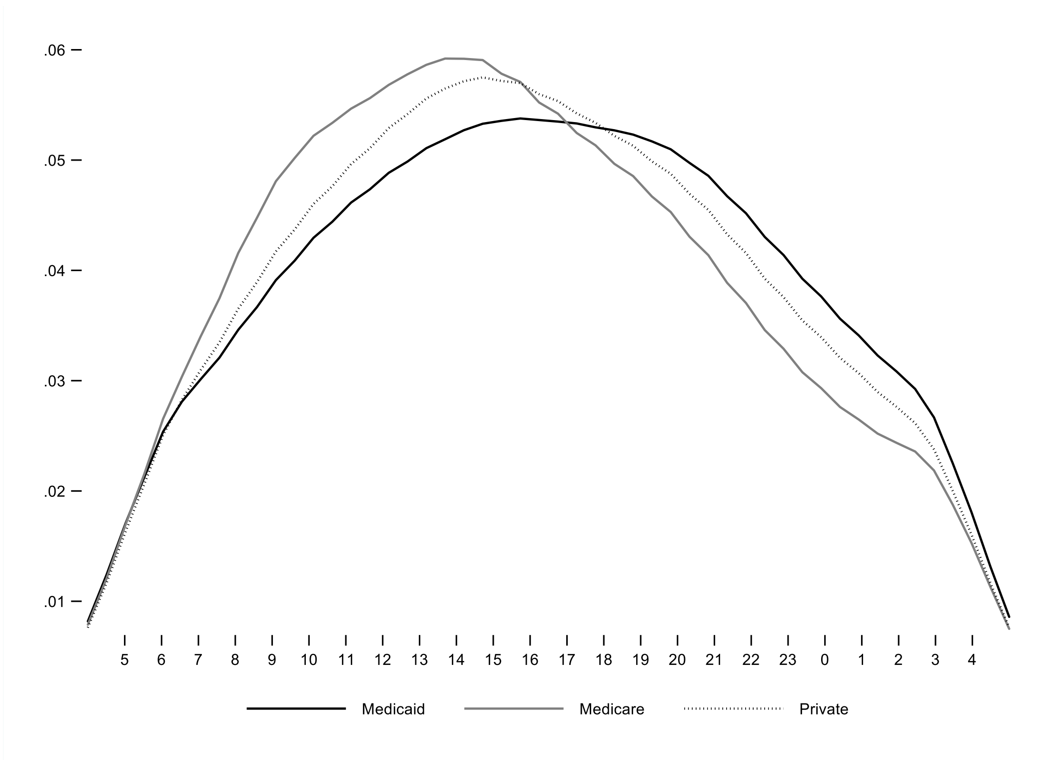


Figure A2. Distribution of Number of Calls per Day of the Week by Primary Method of Pay

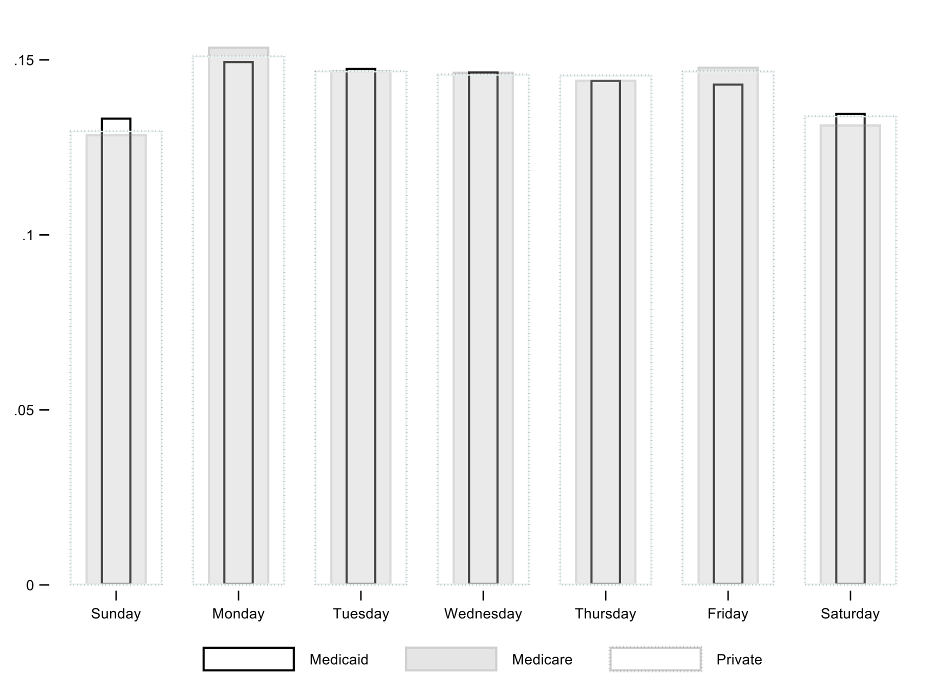
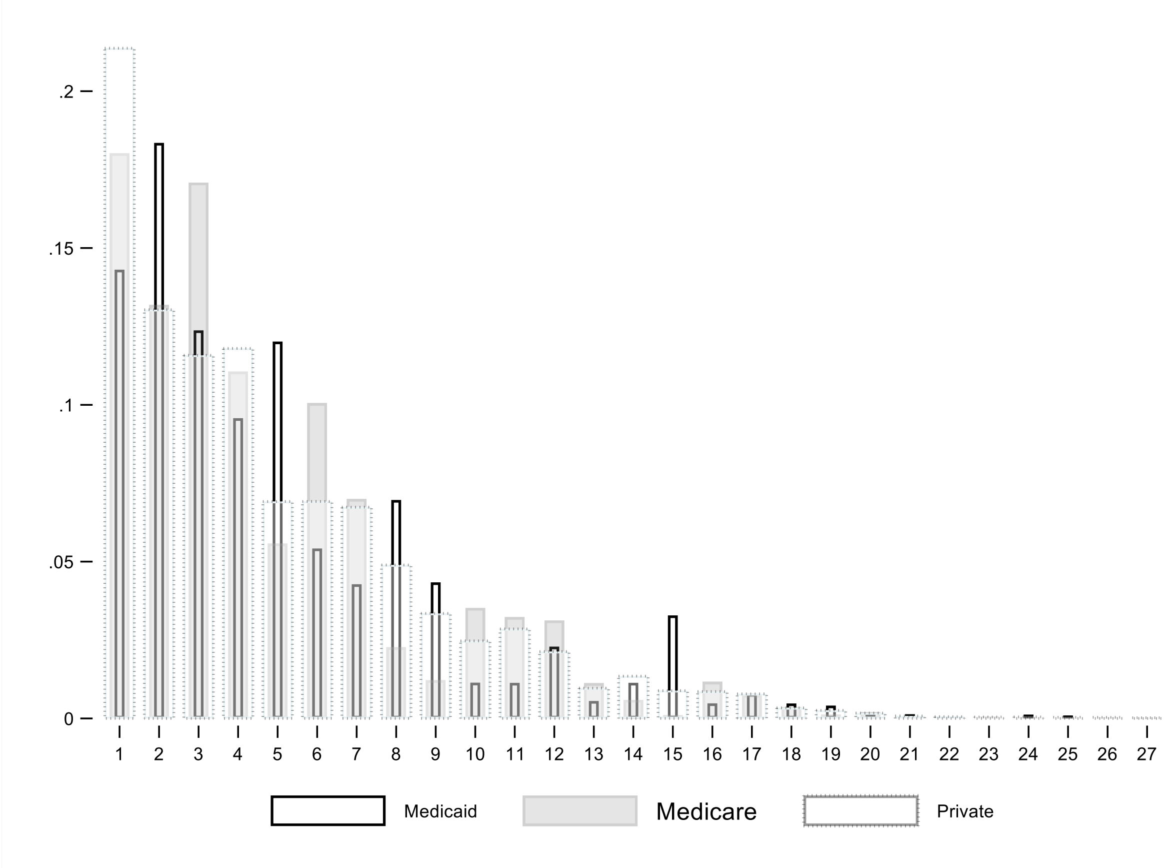


Figure A3. Distribution of Patients' Conditions (Provider Primary Impression) by Primary Method of Pay



1 Traumatic injury
2 Abdominal pain / problems
3 Respiratory distress
4 Chest pain / discomfort
5 Behavioral / psychiatric
6 Altered level of conscious
7 Syncope / fainting
8 Seizure
9 Poisoning / drug ingestion
10 Stroke
11 Cardiac rhythm disturbance
12 Diabetic symptoms
13 Cardiac arrest
14 Allergic reaction
15 Pregnancy / OB delivery
16 Hypovolemia / shock
17 Hyperthermia
18 Airway obstruction
19 Vaginal hemorrhage
20 Respiratory arrest
21 Stings / venomous bites
22 Hypothermia
23 Obvious death
24 Electrocution
25 Sexual assault / rape
26 Inhalation injury
27 Smoke inhalation

Figure A4 (a). Coefficient Estimates of Procedures Performed by Organization Type

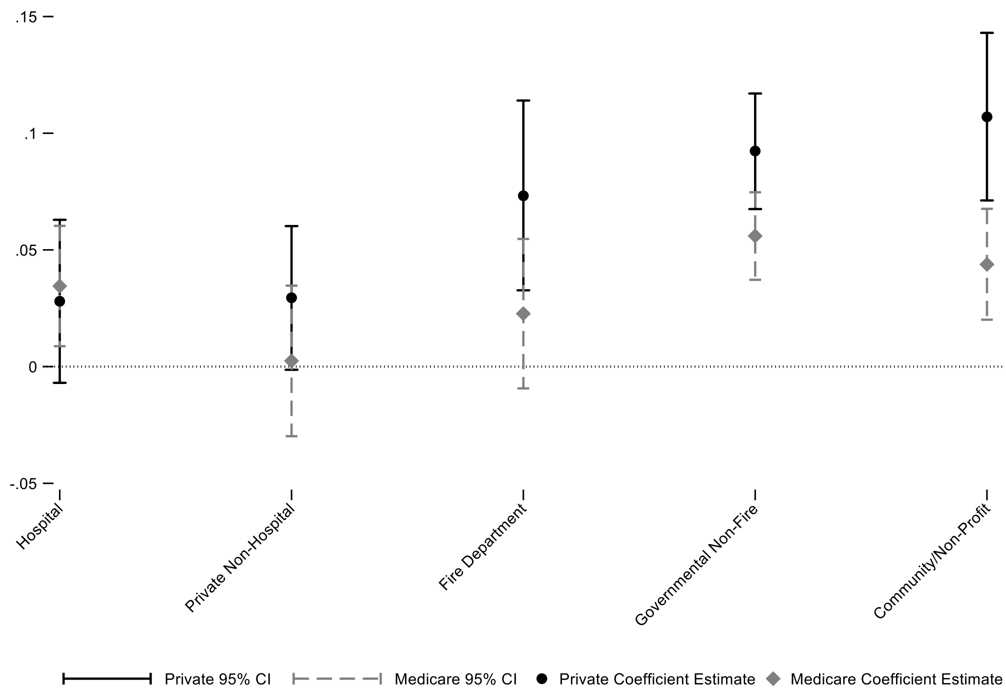


Figure A4 (b). Coefficient Estimates of Time with Patient by Organization Type

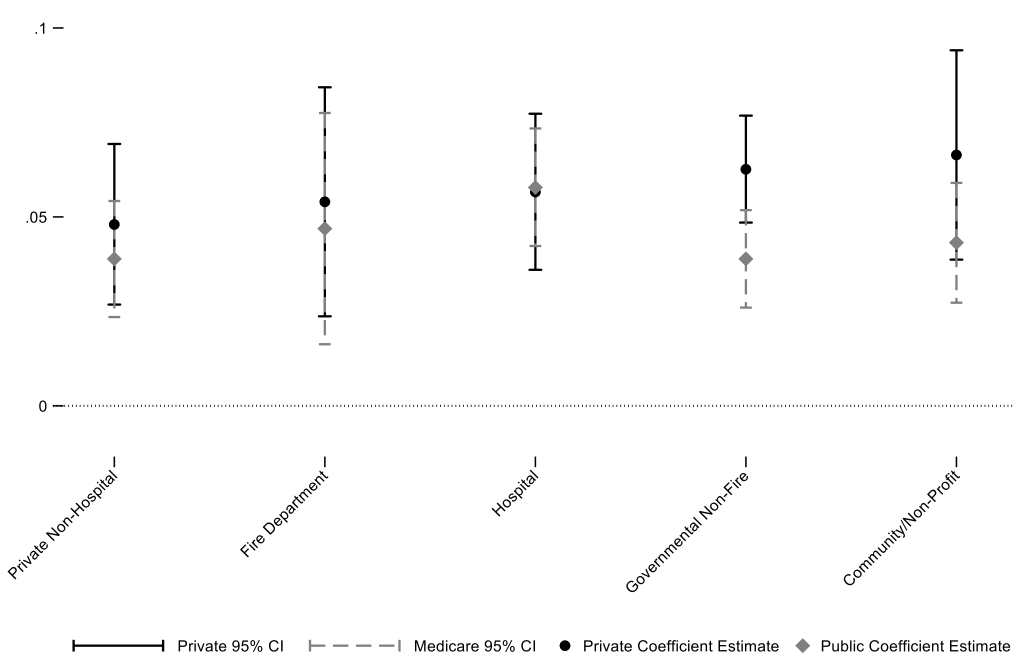


Table A1. Poisson Regression of Patient Insurance Type on Procedures Performed (Count Variable)

	(1)	(2)	(3)	(4)
	Log (procedures)	Log (procedures)	Log (procedures)	Log (procedures)
Medicare	0.146	0.147	0.056	0.033
	(0.002)	(0.002)	(0.002)	(0.002)
	[0.000]	[0.000]	[0.000]	[0.000]
Private Insurance	0.163	0.161	0.127	0.089
	(0.002)	(0.002)	(0.002)	(0.002)
	[0.000]	[0.000]	[0.000]	[0.000]
Unit FE	Y	Y	Y	Y
Time Controls		Y	Y	Y
Patient Controls			Y	Y
Call Controls				Y
N	12,642,016	12,642,016	10,545,562	6,033,304
Chi-squared	6,504	9,323	15,125	35,282

Notes. All models use maximum likelihood Poisson regression with fixed effects at the unit level. Robust standard errors in parentheses. P-values in square brackets. The dependent variables are number of procedures count/non-logged. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers , logged response time, reason for choosing destination FE, provider primary impressions FE).

Table A2. The Moderating Effects of Agency Size

	(1) Log (procedures)	(2) Log (time)	(3) Log (procedures)	(4) Log (time)
Unit Count Log (UCL)	0.021	-0.005	0.021	-0.010
	(0.017)	(0.003)	(0.017)	(0.003)
	[0.204]	[0.080]	[0.195]	[0.001]
Medicare	0.019	0.039	0.011	0.006
	(0.003)	(0.003)	(0.014)	(0.009)
	[0.000]	[0.000]	[0.457]	[0.533]
Private Insurance	0.061	0.053	0.075	0.046
	(0.003)	(0.003)	(0.011)	(0.004)
	[0.000]	[0.000]	[0.000]	[0.000]
Medicare x UCL			0.003	0.011
			(0.005)	(0.003)
			[0.550]	[0.001]
Private x UCL			-0.005	0.002
			(0.004)	(0.002)
			[0.229]	[0.254]
Constant	0.487	2.953	0.445	2.965
	(0.083)	(0.054)	(0.083)	(0.051)
	[0.000]	[0.000]	[0.000]	[0.000]
Unit RE	Y	Y	Y	Y
Time Controls	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y
N	6,067,231	5,639,533	6,067,231	5,639,533
R-sq.	0.164	0.158	0.164	0.158

Notes. All models use generalized least squares with unit level random effects specification. Robust standard errors in parentheses. P-values in square brackets. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers , logged response time, reason for choosing destination FE, provider primary impressions FE, *state FE*).

Table A3. Regression Estimates Using Sub-Samples

	Admitted Patients		Lights and Sirens		22:00PM-6:00AM		12:00AM-1:00AM	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (procedures)	Log (time)	Log (procedures)	Log (time)	Log (procedures)	Log (time)	Log (procedures)	Log (time)
Medicare	0.023	0.051	0.022	0.027	0.018	0.042	0.019	0.051
	(0.011)	(0.011)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)
	[0.027]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Private Insurance	0.054	0.072	0.047	0.031	0.060	0.061	0.064	0.067
	(0.012)	(0.010)	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	1.170	2.671	0.423	2.940	0.597	2.822	0.616	2.870
	(0.287)	(0.089)	(0.033)	(0.030)	(0.030)	(0.022)	(0.084)	(0.069)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
Time Controls	Y	Y	Y	Y	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y	Y	Y	Y	Y
N	29,268	28,539	1,157,752	1,071,574	1,607,228	1,493,854	200,004	186,560
Adj. R-sq.	0.06	0.114	0.121	0.083	0.128	0.108	0.133	0.11

Notes: All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. P-values in square brackets. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers, logged response time, reason for choosing destination FE, provider primary impressions FE).

Table A4. Regression Estimates Using Condition Codes as Proxies for Patients Conditions

	(1) Log (procedures)	(2) Log (time)	(3) Log (procedures)	(4) Log (time)	(5) Log (procedures)	(6) Log (time)
Medicare	0.018	0.042	0.018	0.042	0.018	0.042
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Private Insurance	0.056	0.058	0.056	0.058	0.056	0.058
	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.627	2.815	0.626	2.815	0.625	2.813
	(0.029)	(0.016)	(0.029)	(0.016)	(0.030)	(0.016)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Unit FE	Y	Y	Y	Y	Y	Y
Time Controls	Y	Y	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y	Y	Y
N	3,440,045	3,284,589	3,421,551	3,276,014	3,365,191	3,229,741
Adj. R-sq.	0.129	0.103	0.129	0.103	0.13	0.103

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. P-values in square brackets. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers, logged response time, reason for choosing destination FE, condition *code FE instead of provider primary impression FE*).

Models 1 and 2 are based on all 911 calls. Models 3 and 4 are based on 911 calls that resulted in transport. Models 5 and 6 are based on 911 calls that resulted in transport by transport units only. A provider's primary impression captures the initial perspective under which the EMS unit operated. The primary symptom provides insight into the most prominent symptom on which the crew focused its attention. Finally, a patient's condition code provides a post-facto evaluation of the patient's condition from a billing perspective. Neither of the three measurements is perfect in capturing the objective severity of a patient's condition.

Table A5. Regression Estimates Using All 9-1-1 Calls

	(1) Log (procedures)	(2) Log (time)	(3) Log (procedures)	(4) Log (time)	(5) Log (procedures)	(6) Log (time)	(7) Log (procedures)	(8) Log (time)
Medicare	0.075	0.113	0.074	0.112	0.029	0.053	0.018	0.039
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Private Insurance	0.095	0.096	0.094	0.096	0.077	0.074	0.060	0.055
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.756	3.239	0.641	3.195	0.655	3.152	0.736	2.834
	(0.003)	(0.003)	(0.020)	(0.007)	(0.022)	(0.009)	(0.029)	(0.013)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
Time Controls			Y	Y	Y	Y	Y	Y
Patient Controls					Y	Y	Y	Y
Call Controls							Y	Y
N	23,160,984	19,733,847	23,160,984	19,733,847	19,068,939	16,460,385	10,427,620	9,660,370
Adj. R-sq.	0.004	0.011	0.01	0.013	0.016	0.021	0.114	0.097

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. P-values in square brackets. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers , logged response time, reason for choosing destination FE, provider primary impressions FE).

Table A6. Regression Estimates Using 9-1-1 Calls that Resulted in Transport

	(1) Log (procedures)	(2) Log (time)	(3) Log (procedures)	(4) Log (time)	(5) Log (procedures)	(6) Log (time)	(7) Log (procedures)	(8) Log (time)
Medicare	0.088	0.113	0.088	0.112	0.031	0.053	0.018	0.039
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Private Insurance	0.101	0.096	0.100	0.095	0.082	0.074	0.061	0.055
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.779	3.238	0.711	3.194	0.679	3.151	0.740	2.828
	(0.003)	(0.003)	(0.020)	(0.007)	(0.023)	(0.009)	(0.028)	(0.013)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
Time Controls			Y	Y	Y	Y	Y	Y
Patient Controls					Y	Y	Y	Y
Call Controls							Y	Y
N	21,653,092	19,621,351	21,653,092	19,621,351	18,053,036	16,369,098	10,334,834	9,624,394
Adj. R-sq.	0.005	0.011	0.011	0.013	0.017	0.021	0.116	0.097

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. P-values in square brackets. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers , logged response time, reason for choosing destination FE, provider primary impressions FE).

Table A7. Regression Estimates for All Patients Excluding Those 65 and Above with Private Insurance

	(1) Log (procedures)	(2) Log (time)	(3) Log (procedures)	(4) Log (time)	(5) Log (procedures)	(6) Log (time)	(7) Log (procedures)	(8) Log (time)
Medicare	0.085	0.116	0.085	0.115	0.020	0.055	0.008	0.039
	(0.005)	(0.006)	(0.005)	(0.006)	(0.002)	(0.003)	(0.002)	(0.003)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Private Insurance	0.088	0.067	0.087	0.067	0.092	0.065	0.070	0.050
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.742	3.236	0.643	3.202	0.597	3.161	0.663	2.858
	(0.004)	(0.004)	(0.015)	(0.009)	(0.016)	(0.012)	(0.023)	(0.016)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
Time Controls			Y	Y	Y	Y	Y	Y
Patient Controls					Y	Y	Y	Y
Call Controls							Y	Y
N	11,257,935	10,323,558	11,257,935	10,323,558	9,366,792	8,529,916	5,413,521	5,036,133
Adj. R-sq.	0.005	0.013	0.013	0.015	0.019	0.02	0.119	0.095

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. P-values in square brackets. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers , logged response time, reason for choosing destination FE, provider primary impressions FE).

Table A8. Regression Estimates for Patients 65 and Above

	(1) Log (procedures)	(2) Log (time)	(3) Log (procedures)	(4) Log (time)	(5) Log (procedures)	(6) Log (time)	(7) Log (procedures)	(8) Log (time)
Medicare	0.105	0.043	0.105	0.043	0.109	0.038	0.082	0.025
	(0.014)	(0.003)	(0.013)	(0.003)	(0.011)	(0.003)	(0.011)	(0.002)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Private Insurance	0.162	0.057	0.158	0.057	0.153	0.052	0.123	0.034
	(0.015)	(0.003)	(0.014)	(0.003)	(0.012)	(0.003)	(0.012)	(0.002)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	1.718	3.337	1.446	3.317	1.948	3.393	1.976	3.063
	(0.013)	(0.002)	(0.043)	(0.005)	(0.051)	(0.016)	(0.111)	(0.031)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
Time Controls			Y	Y	Y	Y	Y	Y
Patient Controls					Y	Y	Y	Y
Call Controls							Y	Y
N	6,115,457	5,587,876	6,115,457	5,587,876	5,221,315	4,751,524	2,875,552	2,675,678
Adj. R-sq.	0.001	0.001	0.011	0.002	0.015	0.003	0.112	0.077

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. P-values in square brackets. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers , logged response time, reason for choosing destination FE, provider primary impressions FE).

Table A9. Effects of Minority on Procedures Performed and Time with Patient

	(1) Log (procedures)	(2) Log (time)	(3) Log (procedures)	(4) Log (time)
Minority	-0.029	-0.035	-0.025	-0.032
	(0.002)	(0.003)	(0.002)	(0.003)
	[0.000]	[0.000]	[0.000]	[0.000]
Insurance Type Dummies			Y	Y
Constant	0.678	2.885	0.642	2.858
	(0.023)	(0.015)	(0.024)	(0.015)
	[0.000]	[0.000]	[0.000]	[0.000]
Unit FE	Y	Y	Y	Y
Time Controls	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y
N	6,067,231	5,639,533	6,067,231	5,639,533
Adj. R-sq.	0.116	0.093	0.118	0.096

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. P-values in square brackets. The dependent variables are logged number of procedures and logged patient time. Minority is a dummy variable coded as 0 if the patient is white and 1 otherwise. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (gender FE, age) and call controls (logged number of barriers, logged response time, reason for choosing destination FE, provider primary impressions FE). Models 1 and 2 do not include insurance type dummies. Models 3 and 4 include insurance type dummies.

Table A10. Regression Estimates for White Patients Only

	All White		White & Not Home Only		All White	
	(1)	(2)	(3)	(4)	(5)	(6)
	Log (procedures)	Log (time)	Log (procedures)	Log (time)	Log (procedures)	Log (time)
Medicare	0.025	0.042	0.028	0.051	0.021	0.045
	(0.003)	(0.002)	(0.005)	(0.005)	(0.002)	(0.002)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Private Insurance	0.066	0.056	0.083	0.078	0.053	0.056
	(0.003)	(0.003)	(0.005)	(0.004)	(0.003)	(0.002)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Not Home					0.001	-0.093
					(0.007)	(0.005)
					[0.842]	[0.000]
Medicare × Not Home					0.013	-0.009
					(0.005)	(0.006)
					[0.012]	[0.152]
Private Insurance × Not Home					0.049	0.027
					(0.006)	(0.005)
					[0.000]	[0.000]
Constant	0.724	2.847	0.769	2.836	0.700	2.843
	(0.025)	(0.026)	(0.063)	(0.056)	(0.028)	(0.018)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Unit FE	Y	Y	Y	Y	Y	Y
Time Controls	Y	Y	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y	Y	Y
N	4,425,750	4,115,812	626,176	587,882	3,178,574	2,972,172
Adj. R-sq.	0.113	0.098	0.114	0.081	0.122	0.115

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. P-values in square brackets. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. The "Not Home" defined as incident occurred in either (1) industrial place and premises, (2) place of recreation or sport, (3) street or highway, (4) public building, or (5) trade or service (business). Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers , logged response time, reason for choosing destination FE, provider primary impressions FE).

Table A11. Instrumental Variable Estimation

	First Stage	Second Stage	
	(1)	(2)	(3)
	Private insurance	Log (procedures)	Log (time)
3MMA Private Call Ratio by Agency	0.822		
	(0.016)		
	[0.000]		
Private Insurance		0.049	0.029
		(0.002)	(0.002)
		[0.000]	[0.000]
First Stage Predicted Values		0.017	0.002
		(0.099)	(0.013)
		[0.866]	[0.848]
Constant	0.369	0.635	2.864
	(0.017)	(0.073)	(0.018)
	[0.000]	[0.000]	[0.000]
Unit FE	Y	Y	Y
Time Controls	Y	Y	Y
Patient Controls	Y	Y	Y
Call Controls	Y	Y	Y
N	6,067,370	6,067,231	5,639,533
Adj. R-sq.	0.071	0.117	0.095

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. P-values in square brackets. First stage independent variable is private insurance coded as 0 and 1 otherwise. The second stage dependent variables are logged number of procedures and logged patient time. The base insurance category is public insurance (Medicaid and Medicare). Three Month Moving Average (3MMA) Private Call Ratio by Agency is defined as the mean ratio of private to insurance calls over the past month serviced the agency. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers, logged response time, reason for choosing destination FE, provider primary impressions FE).